



A Dual-Branch Convolutional Neural Network with Gated Recurrent Units Network for Enhanced Multimodal Stress Monitoring from Wearable Physiological Signals

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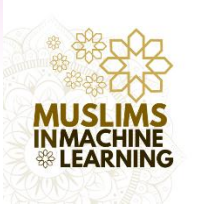
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Objectives

- ❑ Design a **lightweight** deep learning model for stress detection.
- ❑ Optimize for real-time inference on wearable devices.
- ❑ Use **raw BVP and EDA** signals as direct input.
- ❑ Avoid **hand-crafted** features to ensure simplicity and generalizability.

Materials and Methods

Dataset

- ❑ Utilized the publicly available **WESAD** (Wearable Stress and Affect Detection) dataset [1].
- ❑ Includes BVP and EDA signals sampled at **64 Hz and 4 Hz respectively** from **15 subjects**.

Signal Preprocessing

- ❑ **30s** non-overlapping segments.
- ❑ **Normalization** (zero mean, unit variance).
- ❑ Sliding window-based **minority class augmentation**.

Deep Learning Model

- ❑ Implements a dual-path architecture.
- ❑ Contains only **.43M parameters (1.64 MB)**.

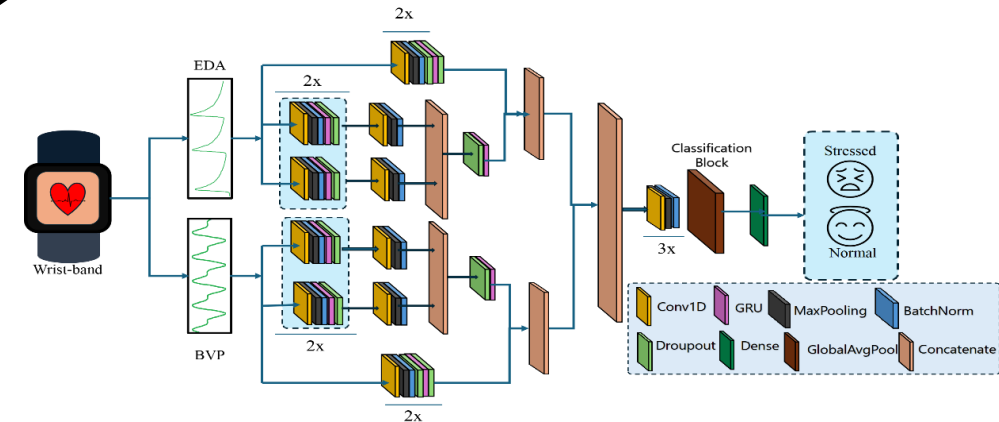


Figure 1: Architecture of the proposed lightweight deep learning model for stress monitoring.

Results

True Label	Without Augmentation		With Augmentation	
	Normal	Stressed	Normal	Stressed
Normal	0.9887	0.0113	0.9925	0.0075
Stressed	0.0492	0.9508	0.0076	0.9924
Predicted Label			Predicted Label	

Figure 2: Normalized confusion matrices of the LOSO cross validation without (left) and with augmentation (right).

Results (Contd')

Table I: The performance scores using LOSO cross-validation, with and without augmentation, are reported for accuracy, F1 score, specificity, sensitivity, AUC, and Cohen's kappa (κ) in (%).

Aug	Acc	Spe	Sen	F1	AUC	k
No	97.53	98.87	95.08	96.14	98.47	94.34
Yes	99.27	99.25	99.29	99.97	99.68	98.40

- ❑ Strong validation performance was achieved.
- ❑ Data augmentation significantly enhanced the results.

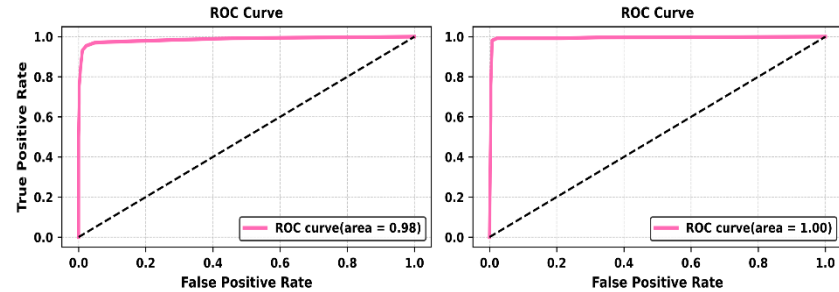


Figure 3:ROC curves showing AUC values of 0.98 for without augmentation (left) and 0.99 for with augmentation(right), highlighting the model's robust performance.

Discussion

Table II: Ablation study results showing the performance of individual signals (EDA and BVP) instress classification. Accuracy (Acc), specificity (Spe), sensitivity (Sen), F1-score (F1), AUC, andCohen's κ are reported in percentages (%).

Signal	Acc	Spe	Sen	F1	AUC	k
BVP	97.37	98.11	96.21	96.01	98.93	94.05
EDA	93.55	94.34	92.05	90.47	95.95	85.61
BVP + EDA	99.27	99.25	99.29	99.97	99.68	98.40

- ❑ Multimodal BVP+EDA delivers the best overall results, surpassing single-signal models.

Table III: Comparison with existing literature.

Study	Dataset	Signal	Accuracy
[2]	WESAD	BVP, EDA,ACC, TEMP	87.12
[3]	WESAD	EDA, EEG,PPG	87.40
[4]	WESAD	PPG	94.90
This Work	WESAD	EDA, BVP	99.27

- ❑ Our method achieves the highest accuracy compared to existing studies.

Conclusions

- ❑ Lightweight CNN-GRU model using BVP signals.
- ❑ Achieves 99.27% accuracy and strong overall performance.
- ❑ Promising for continuous, non-invasive stress monitoring.
- ❑ Future work on multi-class classification and deployment on resource constrained devices.

Bibliography

- [1] Schmidt, P., Reiss, A., Duerichen, R., Marberger, C., and Van Laerhoven, K. Introducing WESAD, a multimodal dataset for wearable stress and affect detection. In *Proceedings of the 2018 ACM International Conference on Multimodal Interaction (ICMI)*, pp. 400–408, 2018.
- [2] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, “Introducing wesad,a multimodal dataset for wearable stress and affect detection,” in *Proceedings of the 20th ACMinternational conference on multimodal interaction*, pp. 400–408, 2018.
- [3] P. Siirtola, “Continuous stress detection using the sensors of commercial smartwatch,” in *Adjunctproceedings of the 2019 ACM international joint conference on pervasive and ubiquitouscomputing and proceedings of the 2019 ACM international symposium on wearable computers*,pp. 1198–1201, 2019.
- [4] M. S. Ali, M. A. Motin, and M. Mahmud, “A dual path hybrid convolutional neural networkand bidirectional long-short term memory approach for ppg-based stress monitoring,” in *4thMuslims in ML Workshop co-located with ICML 2025*.